Information Dispersion and Auction Prices

March 19, 2005

Abstract

Do bidders behave as auction theory predicts they should? How do bidders (and thus, prices) react to different types of information? This paper derives implications of auction theory with respect to the dispersion of private information signals in an auction. I conduct a survey of non-bidders to construct a measure of information dispersion that is independent of bidding data. This permits joint tests of Bayesian-Nash equilibrium bidder behavior and information structure (common vs. private value) in a sample of eBay auctions for computers. The measure also allows me to separately estimate the price effects of seller reputation and product information. eBay prices appear consistent with Bayesian-Nash common value bidding behavior. Uncertainty about the value of goods due to information dispersed over auction participants plays a larger role than uncertainty about the trustworthiness of the sellers, but both are significant drivers of price. Thus, seller reputation complements, rather than substitutes for, information provided in the auction descriptions by lending credibility to that information, creating an incentive for sellers to reduce uncertainty in their auctions. (*JEL* C42, D44, D8, D82, L14, L15, L86)

[0]I would like to thank Pat Bajari, Tim Bresnahan, Susan Athey, Ed Vytlacil, and Ali Hortaçsu; Paul Hartke for scripting; Tiffany Chow, Yi-Xuan Huynh, Steve Yuan for their research assistance; and The John M. Olin Foundation through the Stanford Institute of Economic Policy Research and Stanford School of Humanities and Sciences Graduate Research Opportunities Grant for their financial support. Any mistakes in the paper are completely my own; comments and suggestions are very welcome.

This paper addresses two important and challenging questions about the use of auctions in commercial markets: "Do bidders behave in the way that theory predicts they should?" and "What are the effects of different types of information on prices?" These questions are relevant to both government and industry, who have traditionally employed auctions to price and allocate assets and contracts with high but unknown value, and the millions of people have been able to participate via the Internet in auctions for goods that are often of unknown value (e.g., used goods, unknown brands). The answers to these questions suggest the appropriate conditions under which auctions can be employed most effectively.

In theory, by solving sophisticated Bayesian-Nash (Nash) equilibrium bidding strategies, auction participants have benefited from the ability of the auction mechanism to elicit prices which reflect the true but unknown common value of the good from bidders who only possess private information signals about the value of the good. (Wilson 1977) These strategies involve accounting for the dispersion of information signals and number of bidders. Bidders that fail to do this may suffer the "winner's curse," where the highest bidder wins the auction at a price greater than the common value of the good. The challenge to determining whether commercial auctions are consistent with theory is that tests thus far have had to assume either that bidders a) play these equilibrium strategies or b) treat their private information as having common value rather than treat it as a reflection of their private value for the good. The assumption that participants solve complex bid functions may be particularly suspect for participants in mass-market online auctions.

This paper produces a procedure for testing both assumptions concurrently by examining price responses to changes in information dispersion and the number of participants in auctions. The procedure involves testing implications of auction theory with respect to information dispersion that are derived using results from Milgrom & Weber (1982, henceforth referred to as MW). These tests require a measure of information dispersion that does not rely on assumptions about bidder strategies or whether the setting is private or common values. I constructed an "external" measure of information dispersion by conducting a survey among non-bidders. The survey asked people to view product descriptions of auctioned items and report what they thought was the most the item was worth. I used the standard deviation of responses for each auction description to estimate the dispersion of information in each auction.

In practice, the bidder deals with different types of information: information about the seller and information about the good (as provided by the seller and as gathered from the bidder's own experiences).Seller-rating mechanisms offer natural measures for reputation, but information about a good is challenging to quantify. As a result, while a growing empirical literature has exploited seller reputation in online auctions and focused on information asymmetry between bidders and sellers as a barrier to trade[1], the role of product information and the price effects of uncertainty over the value of a good due to information dispersed over all auction participants has largely been ignored. If this type of uncertainty is important, the previous work may suffer from omitted variable bias. The survey-based measure of information dispersion serves as a measure of amount of product information available to the bidder, permitting estimation of price effects that distinguish between seller reputation and product information. This permits estimation of the importance of information dispersion relative to information asymmetry in these markets. Empirical work in market has found that reputation and product information can be substitutes. (Anand & Shachar 2004a, 2004b) By estimating the interaction effect of these two types of information, it is also possible to determine whether the same holds true in these markets.

I apply my process for measuring information dispersion to a sample of eBay online auctions to test theory and estimate the price effects of different types of information. I find that eBay prices are consistent with Nash equilibrium behavior in a common values setting and that winners do not suffer from the winner's curse. I find evidence that information dispersion is more important than information asymmetry in these markets, since changes

[1] In general, this work has found the price effect of reputation to be small. (Reiley, Bryan, Prasad & Reeves 2000; Houser & Wooders 2000; Melnik & Alm 2002; McDonald & Slawson, Jr. 2002; Livingtson 2002; Eaton 2002; Resnick, Zeckhauser, Swanson & Lockwood 2004; Jin & Kato 2004) A summary of the empirical work appears in Resnick, Zeckhauser, Swanson & Lockwood 2004.

in product information provided by the seller have a larger effect on price than reputation, but both are important. Reputation complements, rather than substitutes for, information dispersion on eBay: a good reputation lends credibility to the information provided by the seller. There is an incentive for sellers to both build good reputations and provide more information in their auction descriptions, reducing uncertainty in these markets.

The source of privately dispersed common value information in this market is the differing private information that bidders possess about the reliability of a particular model of computer or its components. Private value information (e.g., heterogenous preferences over computers) is likely dispersed in this market as well. Fortunately, my tests allow me to distinguish Nash equilibrium behavior in a common values setting (Nash CV) from the alternatives of naïve bidding in a common values setting (naïve CV) and bidding in a private values settings (PV), so I do not need to make any assumptions about whether the CV or PV component dominates this market. Sellers provide product descriptions in the auction listing that may decrease the level of information dispersion by sharing private information publicly. The level of detail in those descriptions differs across auctions, so the level of information dispersion varies across auctions in my sample. This variation helps identify the effect of changes in information dispersion on price.

This approach has several advantages compared to other approaches in the literature which test for Nash behavior or common versus private values, but rarely both.

Some experimental literature has tested equilibrium bidding behavior by directly controlling the primitives. Kagel, Levin & Harstad (1995) find that while prices rise as predicted by theory when information is publicly released in CV auctions with fewer bidders, prices fall in larger auctions.[2] Although bidders may be attempting to play Nash equilibrium strategies, they may not get the magnitudes right. However, contrary to Nash CV, increasing the

[2] In experimental auctions with 4-5 and 6-7 bidders, Kagel, Levin & Harstad (1995) provide bidders with a private signal on a common value item, and then release a public signal after a first round of bids on the item and allow bidders to update their bids.

number of bidders does not change the bids.[3] Most analogous to my work is a study by Goeree and Offerman (2002), who test the reaction of prices when the range of signals is compressed. Prices fall with increased dispersion, but by less than theory predicts.[4]

Studies of commercial auctions have not yet employed tests exploiting information dispersion. As a result, the majority of the literature has focused on either testing for common versus private values or testing for rational bidding behavior, but not both concurrently. The literature testing for Nash equilibrium behavior has often assumed a common or private values setting, allowing authors to relate ex post values to ex ante bids to draw inferences about strategic bidding.[5] In only a few cases have ex post values been available, and these values are typically measured with error compared to the true value.[6] Even with these assumptions and ex post information on values, the underlying parameters are just identified, so any further tests of bidder behavior or comparative static estimates cannot be conducted.[7]

The literature testing between common value and private value settings has often assumed Nash equilibrium behavior.[8] Authors have then explored how variation in the number of bidders can be used to test between private and common value settings, since the winner's

[3]Bidders also fail to account for the winner's curse in ascending oral auctions. (Kagel & Levin 1991) Other experimental tests (Kagel & Levin 1991, Lind & Plott 1991, Cox & Smith 2001) suggest that this failure is not the result of strategic considerations with respect to budgets. Even experienced commercial bidders may fail to shade correctly in experiments, as found in Dyer, Kagel & Levin (1989) which employs construction industry bidders as subjects.

[4]Goeree & Offerman (2002) conduct auctions with low and high distributions of signals for 3 bidders, but only conduct high distributions of signals for auctions with 6 bidders. They thus are not able to fully study the interaction effect between variance and the number of bidders.

[5]McAfee, Takacs & Vincent (1999) use ex post values to test the information aggregation properties of auction prices. (McAfee, Takacs & Vincent 1999) In their seminal paper, Hendricks & Porter (1988) showed that bidders with superior information make a profit in auctions, whereas uninformed bidders account for the winner's curse and get zero profits. Athey & Levin (2001) show that bidders respond strategically to private information about the species composition in timber auctions.

[6]In fact, different conclusions regarding whether bidders actually avoided the winner's curse as evidence of equilibrium bidding behavior in oil tract lease auctions has been attributed to measurement error. (Capen, Clapp & Campbell 1971; Mead, Moseidjord & Sorensen 1983; Hendricks, Porter & Boudreau 1987, etc.)

[7]Li, Perrigne & Vuong (2000) also show that the joint distribution of signals and values is identified under some additional functional form assumptions *and* if all bids are observed. Athey & Haile (2002) show that identification fails unless all bids are observed, but that ex post information on the common value combined with partial bid information can identify the primitives in a common value auction. See also Laffont & Vuong (1996); Guerre, Perrigne & Vuong (2000); Li, Perrigne & Vuong (2002).

[8]This empirical literature has been predicated on an extensive theoretical literature identifying empirically testable conditions for private value and common value settings, e.g. Donald & Paarsch (1993);Elyakime, Laffont, Loisel & Vuong (1994); Laffont, Ossard & Vuong (1995); Pinske & Tan (2000);

curse is more severe with more bidders.[9] (Paarsch 1992; Haile, Hong & Shum 2000, Athey & Haile 2002). The challenge to these approaches (and potentially my approach as well) is that the true number of participants may be unobserved and/or endogenously determined. Another approach imposes Nash bidding behavior in order to estimate the joint distribution of information signals and values and determine whether the distributions correspond to common or private values. (Hong & Shum 2002, Bajari & Hortaçsu 2003) The paper most closely related to my work is Hendricks, Pinkse & Porter (2001). Under the assumption of a common values setting, they test whether bids are consistent with Nash equilibrium in a first-price sealed-bid setting. They then exploit ex post information on values to back out the distribution of signals and show that bidder profit margins appear unreasonable under the PV assumption and are more consistent with a CV assumption. This method also does not assume Nash equilibrium behavior. However, it relies on calculated magnitudes rather than comparative statics to distinguish between the CV and PV settings.

My survey data provides information about the distribution of signals independent of the bidding data, so I avoid expending the identifying power of the information available on recovering the distribution of private information signals from the bid data. This allows me to 1) simultaneously distinguish between common and private value settings using comparative statics without imposing Nash equilibrium bidding behavior, 2) distinguish between Nash and naïve bidding behavior using comparative statics without assuming a PV or CV setting, 3) employ only price data from the auctions as opposed to all bids, 4) utilize extra identification power to estimate any potential bias between my measures of dispersion and the true values and estimate other comparative statics of interest. Since I base my assessment of bidding behavior on comparative statics, my benchmark for whether bidders exhibit Nash CV behavior does not require bids to exactly match Nash CV predictions. My benchmark simply requires that bidders react strategically to the number of bidders and dispersion in the direction that theory predicts, and thus permits Nash CV bidder behavior to involve

[9] Laffont & Vuong (1996) show that bidding data alone with a fixed number of bidders is insufficient to distinguish common value settings from affiliated private value settings.

errors in magnitude (which I can then estimate).

The rest of the paper proceeds as follows: Section 1 presents the theoretical model from which the testable implications of information dispersion are derived. Section 2 describes the auction and survey data. Section 3 presents the empirical results. Section 4 estimates the potential winner's curse in these auctions and conducts counterfactual analysis of changes in reputation and information dispersion. The last section draws conclusions.

1 Theory and Empirical Implications

This section presents the theoretical model of Nash CV prices from second-price sealed-bid auctions. It then presents testable, comparative static implications that distinguish between the Nash CV model and the PV/naïve CV model, as well as hypotheses to test regarding reputation and information dispersion (as a measure of product information).

A single, indivisible item is put up for auction. The item has the same, unknown value v to all n risk-neutral bidders, indexed by i.[10] Bidders know the density of v, $f_v(v)$. Each bidder also observes a private signal x_i from a distribution around v. I assume the form of the mineral rights model, where x_i is independently and identically drawn from a distribution centered around v such that the signals x_i are affiliated with the values v. This distribution has commonly known density $f_{x|v}(x_i|v)$.

In a second-price auction, the person who submits the highest bid wins the auction, and pays the amount submitted by the second highest bidder. Losing bidders get zero payoff. Under risk neutrality, the optimal Nash equilibrium bid $b(x_i)$ for symmetric bidders in a sealed-bid auction is

$$b(x_i) = E[v|x_i, \max X_{j\neq i} = x_i], \tag{1}$$

[10] Risk-aversion in the common values setting can be modeled as reductions in bids in response to higher uncertainty (information dispersion). This will not change the sign of any comparative static implications of Nash CV vs. PV/naïve CV.

where $X_{j \neq i}$ denotes the set of all signals excluding x_i. (Milgrom and Weber 1982)

The expected winning price is the expected value of the second order statistic of Equation 1. Let $x^{n-1:n}$ denote the 2nd highest signal from a set of n signals. We can approximate the expected winning price by a function, denoted p, of n and parameters describing $f_{x|v}(x|v)$ and $f_v(v)$. For distributions which can be characterized by scale and location, we denote the standard deviations of $f_{x|v}(x|v)$ and $f_v(v)$ by $\sigma_{x|v}$,and σ_v, respectively, and the means of $f_{x|v}(x|v)$ and $f_v(v)$ by v and μ_v, respectively.

$$E[b(x^{n-1:n})] \approx p(n, v, \sigma_{x|v}, \mu_v, \sigma_v). \tag{2}$$

I use the function p to establish comparative static results from auction theory in the rest of this section.

I chose the second-price sealed-bid model for eBay auctions for several reasons. During the eBay auctions, bidders can see the current price: the second-highest bid plus one increment. The winner is the bidder who submits the highest bid. Bidders are free to enter and exit at any time as well as update and resubmit their bids before the close of the auction. Harstad & Rothkopf (2000) found that English auctions with re-entry are more closely approximated by second-price sealed bid models. Empirical observations of the timing of bids on eBay indicate that the majority of auctions in all categories experience a flurry of bidding during the last minutes.[11] To the extent that insufficient time exists to view all the information contained in those bids before the close of the auction, the auction tends to operate like the second-price sealed-bid model.

1.1 Implications of Nash CV auctions

MW showed that in equilibrium, if the seller publicly reveals a signal drawn from the same distribution as those of the bidders' signals, then prices will rise in a second-price sealed-

[11] Bajari & Hortaçsu (2004) review empirical findings in online auction settings.

bid common value auction.[12] Public revelation is equivalent to a seller providing more information in the auction description. The effect of publicly revealing more information is a reduction in information dispersion, reflected in $\sigma_{x|v}$. For example, as soon as bidders see "Computer Brand A" in the auction description, their signals will be dispersed due to differences in private information about the fan noise and clear wiring for Computer Brand A. However, if the auction description also says "fan is noisy, clear wiring makes it easy to install more memory", the differences in information have been reduced, and so their signals become less dispersed around v. For $n > 2$, prices fall in Nash equilibrium, where bidders account for the less narrow distribution of signals around the common value by shading more.

1. $\dfrac{\partial p}{\partial \sigma_{x|v}} < 0$. The Nash CV price decreases if the dispersion of information signals increases.[13]

Although prices converge to the common value as $n \longrightarrow \infty$, prices may be decreasing or increasing in n away from the limit. (Wilson 1977, Milgrom 1979) As n increases, the value of the highest signal drawn increases. Under Nash CV, bidders should shade more to account for this increase. Whether the draws from the higher distribution will overcome the amount of bid shading depends on both n and the distribution of signals. As a result, prices will be decreasing with respect to n for some values of n and $\sigma_{x|v}$, but increasing for other values.

1.2 Implications of PV and naïve CV auctions

In second-price auctions, prices equal the second highest signal under PV. I define naïve CV as a common value setting where bidders ignore n and $\sigma_{x|v}$, and just bid their signal

[12] MW assume that the signals and common value are affiliated, and that bidders are symmetric and behave rationally. They also assume the existence of some mechanism, such as reputation, which makes the additional information credible to the bidders. The MW public information result will not necessarily hold in first price auctions. (Perry & Reny 1999)

[13] This result is translation of Theorems 8 and 12 of MW. McMillan & Kazumori (2002) prove this result for distributions satistfying affiliation. Rothkopf (1969) discussed the disclosure of information as a way to improve the estimating accuracy of bidders, thus causing procurement prices to fall in first price auctions.

plus some absolute amount or percentage adjustment. By this definition of naïve CV, I distinguish between Nash versus naïve bidding by whether bidders react to n and $\sigma_{x|v}$ such that prices increase or decrease as predicted by Nash, not by whether bidders generate prices exactly equal to the Nash prediction. Therefore, I allow Nash equilibrium behavior to involve errors in magnitude.

I derived the following comparative static implications from analysis of expected values of order statistics under symmetric (e.g. uniform, normal) and lognormal distributions.[14]

2. $\dfrac{\partial p}{\partial \sigma_{x|v}} > 0$ for symmetrically distributed signals. PV and naïve CV prices increase with the dispersion of signals for symmetrically distributed signals. Prices could increase or decrease for lognormally distributed signals.

3. $\dfrac{\partial p}{\partial n} > 0$.[15] PV and naïve CV prices increase with the number of bidders.[16]

1.3 Summary of Predictions

Table 1 summarizes the comparative statics predictions which would permit us to empirically distinguish the auction model generating the data. Each row designates a different model of bidding behavior and information structure. Each column designates a comparative static. Each box in the grid indicates the predicted sign for each comparative static under each model.

The Nash CV model is uniquely identified if prices are decreasing in dispersion and decreasing in the number of bidders. If prices increase with dispersion, then the PV/naïve CV model applies. I do not measure Nash CV behavior by whether or not bids exactly match Nash CV predictions but by whether prices suggest that bidders react to the number

[14] Result derived from analysis of order statistics. (Mood, Graybill & Boes 1974; Balakrishnan & Chen 1999)

[15] Although monotone comparative statics would be more appropriate to use to describe the relationship between n and p, I treat n as a continuous variable and p as continous in n. This is consistent with the empirical application later in the paper: bidders and the econometrician must estimate n, and so they may not be constrained to integers.

[16] Thanks for John Morgan for his notes on order statistics.

Table 1: Comparative statics from auction theory

Model	$\frac{\partial p}{\partial \sigma_{x\|v}}$	$\frac{\partial p}{\partial n}$
PV/naïve CV	$-/+^{*}$	$+$
Nash CV	$-$	$-/+$

*+ for symmetrically distributed signals.

of bidders and dispersion in the way that they should strategically. So I allow Nash CV bidder behavior to involve errors in magnitude.

Comparative statics do not distinguish any of these models from a mix of common and private values, but the empirical estimation will reveal if one component is dominant. If we observe price behavior consistent with Nash CV comparative static implications, we can infer that the common value component is dominant in this market. Anecdotal evidence from eBay computer auctions suggest that the common value component is a dominant component to these products. A flurry of bidding occurs at the end of the auction, and some bidders update their bids. This behavior is theoretically inconsistent with private values auctions, where bidders should not be influenced by other people's bids and therefore should not be updating their bids and gain no advantage from bidding at the last second.

1.4 Hypotheses about Information Asymmetry

MW model public revelation of information as credible statements by a seller of her signal of the object's v. In real-world auctions, sellers can describe the objects in greater detail. Real-world sellers also vary in reputation and therefore in the credibility of their descriptions of objects. Reputation can affect price in two ways: by raising or lowering the expected value of an item (i.e., a reputation premium) and by affecting the way bidders perceive the dispersion of information (i.e., credibility). Reputation may also behave as a substitute for product descriptions: bidders may find that reputation of the seller provides sufficient information about the value of the product. This would be particularly true if information asymmetry was a much larger source of uncertainty than information dispersion.

Work by Akerlof(1970), Klein & Leffler (1981) and Shapiro (1983) suggest that prices should rise with better reputation, denoted r, under non-auction conditions. A seller with a reputation for good transactions may be signaling that she auctions better products.

4. $\dfrac{\partial p}{\partial r} > 0$. The expected common value is directly increasing in reputation.

A reputation for good transactions may also signal that the seller auctions products that meet bidder expectations based on the auction description. The value of the product may be lower, but the seller reveals this information. Holding v constant, I hypothesize that in the CV setting, a seller with a good reputation who reduces information dispersion will reap higher prices as a result of credible reduction in $\sigma_{x|v}$. Even if truthful revelation causes bidders to estimate a lower v than if the seller had remained vague about the faults of the item, the reduced information dispersion means that bidders will not shade their bids even lower. An interesting implication of this hypothesis is that credible sellers should also suffer a more negative price effect from high $\sigma_{x|v}$ than sellers with worse reputations. A seller with a good reputation who provides minimal product information may be perceived by bidders as trying to hide something. For a seller with no credibility, reducing information dispersion makes no difference, because bidders discount the value of information provided by that seller. Consequently, I hypothesize that CV Nash prices will fall with dispersion at a faster rate with better reputations.

5. In Nash CV auctions, the perceived level of information dispersion is increasing in the level of information dispersion provided by the seller at an increasing (decreasing) rate with the seller's (bad) reputation. $\left(\dfrac{\partial^2 p}{\partial \sigma_{x|v} \partial r} < 0\right)$

The alternative hypothesis would reverse the sign on this interaction, suggesting that reputation could compensate for the negative effect of poor product information (high information dispersion) on price. This effect would be consistent with findings by Anand & Shachar (2004a, 2004b) that reputation can substitute for product information.

2 Dataset

Over 5000 new and used computers are listed daily in the personal computer (PC) category by both individuals and businesses. Prices, the eBay-defined overall score for the seller, the number of bidders, and the auction description were collected for 222 eBay PC auctions held between June 24 and July 12, 2002. The auction descriptions were used to create a survey. This section defines the regressors that were drawn directly from the auction data and those generated by the survey.

2.1 eBay Auction Data

Each computer auction is a unit of observation. The auction operates as follows: a seller lists a computer for auction on eBay, setting the minimum bid and the duration of the auction in days, and providing a description of the item being auctioned. She may also choose to set a reserve price, below which the item does not sell, and she may choose to pay for special listing features that could increase the visibility of her auction.

During the auction, potential bidders can observe all of the auction details set by the seller except for the value of the reserve price. They can also observe the seller's overall feedback score, which is the number of auctions for which she received positive feedback minus the number where she received negative feedback. By clicking on that score, bidders may view the breakdown of positive, negative, and neutral feedback that any eBay user has received and whether these feedback were for sales or purchases of items. They may also observe who has already bid in the auction and how many times, but not the amount of the bid.

Bidders observe the current price at all times. When bidders submit bids, the price rises by one bid increment (as defined by eBay rules) above the second highest bid currently submitted. If the increment causes the price to be higher than the highest bid, then the price only rises to the highest bid. Bidders may submit bids at any time and more than once

Table 2: Summary statistics for 222 eBay computer auctions

Variable	mean	median	st. dev.	min	max
price: P_t	$359.01	$255.00	369.16	$9.51	$2802
overall score: $SCORE_t$	680	27	2601	0	19,456
negative score: NEG_t	25.5	2	106	0	785
no. of bidders: N_t	6.5	6	4	2	22

while the auction is still open. In the case of tied bids, the earliest bidder wins.

The summary statistics of data collected from my sample of auctions are presented in Table 2. The price in each auction is denoted P_t, where t indexes the auctions. The number of bidders observed in the auctions is denoted N_t. The overall feedback score of the seller in each auction is denoted $SCORE_t$, and the negative feedback for the seller is recorded separately under NEG_t. The regressors used to capture the effect of the number of bidders and reputation on price will be N_t and a linear combination of $SCORE_t$ and NEG_t. The quadratic term $SCORE_t^2$ is also included to account for diminishing returns to a large feedback score.

I selected auctions to ensure variation in the sellers' overall feedback score. I excluded auctions with less than two bidders and auctions for multiple units of computers. I also excluded auctions which were terminated via "Buy It Now," a feature which allows a bidder to pay a list price for the item and end the auction. The sample size was limited in order to gather more survey responses per auction and reduce depreciation issues by minimizing the time between which all auctions were held.

2.2 Survey Data

To obtain a measure of the mean and dispersion of private signals received by bidders in the auctions, I created a web-based survey. Anyone could respond the survey, except for the actual bidders in my sample of auctions. The survey was distributed to acquaintances by word of mouth during July and August, 2002. I asked people to read the computer

Table 3: Summary statistics for survey on 222 auctions

Variable (831 respondents)	**mean**	**st. dev.**	**min**	**max**
no. of responses/auction	46	6	25	65
average: V_t	\$666.43	317.28	\$101.48	\$1,816.98
standard deviation: SD_t	472.38	153.94	163.57	980.50
average experienced: $V_{e,t}$	\$603.76	351.43	\$46.11	\$1923.08
... inexperienced: $V_{a,t}$	\$682.48	317.59	\$95.97	\$1782.50
st. dev. experienced: $SD_{e,t}$	317.25	171.17	0	1429.78
... inexperienced: $SD_{a,t}$	492.03	168.31	138.94	1074.15

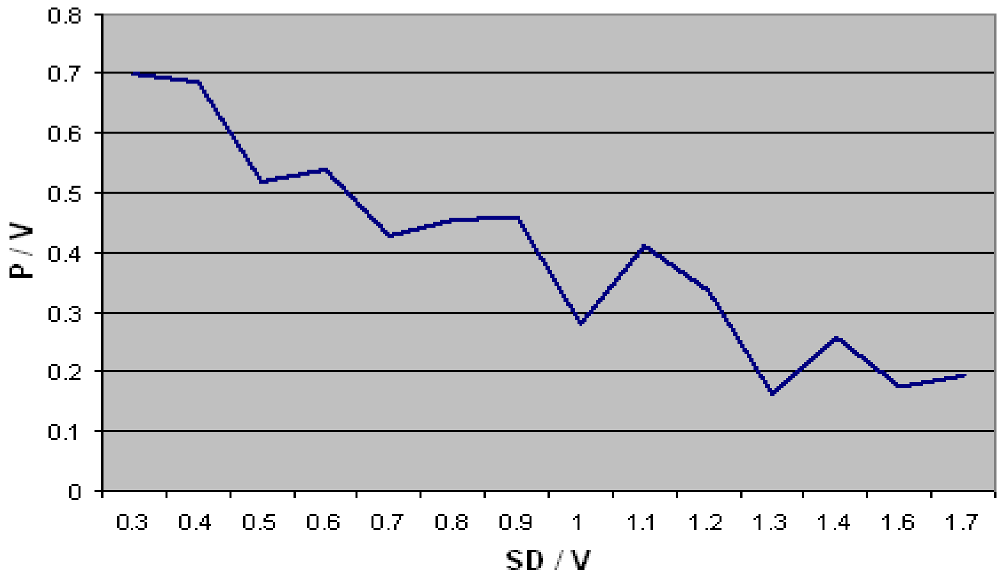
auction descriptions from my sample and then answer the following question: "If a friend wanted to buy the computer described below, what is the most she should pay for it?"(see Appendix A). These descriptions only contained the information provided by the seller in the "descriptions" section. Information listed by eBay about the bids, reservation values, number of bidders, and the seller's identity and reputation were removed.

I also collected background data on survey respondents, asking them about their experience working with computers, purchasing computers, and purchasing computers in online auctions (see Yin 2002 for a full description of the survey procedure). I refer to respondents who have had experience with eBay online auctions for computers as "experienced." Approximately 20 percent of the responses in each auction were from experienced respondents. I refer to the rest of my respondents as "inexperienced."

On average, I collected 46 responses per auction. The average of the responses for each auction, denoted V_t, is is a measure of v_t. The absolute value of the standard deviation of the responses in each auction, denoted SD_t, is a measure of $\sigma_{x|v,t}$. (See Yin 2002 for analysis of V_t and SD_t as measures of v_t.and $\sigma_{x|v,t}$). I also define $V_{e,t}$ and $V_{a,t}$ and $SD_{e,t}$ and $SD_{a,t}$ as the average and standard deviation of responses from the experienced and inexperienced respondents, respectively. Summary statistics from the survey are presented in Table 3.

Figure 1 graphs the unconditional correlation between P_t and SD_t. To control for differ-

Figure 1: Normalized eBay prices P_t vs. normalized information dispersion SD_t
For each auction, eBay prices P_t and standard deviation of survey responses SD_t were divided by the average of survey responses V_t. The auctions were ordered by increasing normalized SD_t, then divided into bins representing 0.1 changes in normalized SD_t. Average normalized P_t were calculated within each bin and reported along the vertical axis. Interpreting SD_t as a measure of information dispersion, the resulting graph shows that prices are negatively correlated with dispersion of information.



ences in computers, I normalized both P_t and SD_t by dividing them by V_t. I then ordered the auctions by increasing normalized SD_t across the horizontal axis and divided the auctions into bins, each representing 0.1 difference in normalized SD_t. Normalized prices were then averaged over the auctions in each bin and plotted on the vertical axis. Prices are falling as my measures of information dispersion increases, a pattern MW predict for Nash CV auctions. In the next section, I control for the other determinants of price and correct for any measurement bias in the survey data in order to formally test whether the Nash CV model is appropriate for eBay online auctions for computers.

3 Estimation

I employ four estimation procedures to robustly test the bidding behavior and information structure in these eBay auctions for computers. In each case, I estimate the price equation, Equation 2. The first case is OLS estimation of the price equation. Results are presented in Column 1 of Table 4.

I specify a polynomial functional form for the price equation that includes quadratic and interaction terms which will allow me to examine the comparative static implications of auction theory.[17] For these estimates, I use N_t as a measure of n_t, V_t as a measure of v_t, and SD_t as a measure of $\sigma_{x|v,t}$. I also include $SCORE_t, SCORE_t^2$, and NEG_t as measures of reputation. Their interaction with $\sigma_{x|v,t}$ will capture the effect of credibility of information dispersion on price. I assume that *a priori* beliefs about the distribution of computer values are the same for all computers in my sample. As a result, I do not include any measures for μ_v and σ_v (I relax this assumption for μ_v later).

There are several reasons why I use parametric rather than non-parametric estimation. I use parametric estimation in order to include covariates in a parsimonious manner. I wish to test hypotheses and comparative static implications of auction theory involving those covariates. I also do not have the number of observations necessary to undertake non-parametric estimation. Finally, having a polynomial functional form approximation for the price equation further simplifies estimation and facilitates the counterfactual analysis I conduct in the next section.

All the signs correspond to predictions of Nash CV bidding. Prices fall as SD_t and N_t, which is inconsistent with PV and naïve CV settings. The positive interaction effect between $N_t \times SD_t$ is not large enough to reverse the negative effects on price of either N_t or SD_t in my sample.

The statistically significant coefficients on $SCORE_t$ and $SCORE_t \times SD_t$ confirm that

[17] I examined the robustness of various orders of polynomials and found no significant improvements from adding higher order terms, including interaction terms.

while a better reputation increases price, a better reputation also exacerbates the effect of information dispersion on price. Since reputation is composed of positive and negative feedback in this case, we expect the signs on NEG_t and $NEG_t \times SD_t$ to be the reverse of the signs on $SCORE_t$ and $SCORE_t \times SD_t$. The marginal effect of a single negative feedback is a magnitude larger than that for a single positive feedback. Although those coefficients are not statistically significant, prices decrease with worse reputations in the sample, but a worse reputation also diminishes the effect of dispersion on price.

The significant coefficients estimated for SD_t and $SCORE_t$ indicated that there is enough variation between the two to separately estimate their effects on price. If reputation were a sufficient statistic for the information set that bidders employ when determining their bids, then we would expect the coefficient on SD_t to be imprecisely estimated or zero. These estimates suggest that product information and reputation both have significant price effects, so information dispersion over auction participants is another important source of uncertainty in addition to information asymmetry between the buyer and the seller.

We would expect prices to be directly proportional to changes in the value of the item. The significance and magnitude of the coefficient 1.05 on V_t suggests that the survey was able to capture the relative value of the auctioned items. Recall that the survey respondents could not view prices when submitting their valuations.

The next set of estimates measures how well the survey was able to capture the absolute value of the items. It allows V_t to be a biased measure of v_t, and SD_t to be a biased measure of $\sigma_{x|v,t}$. It then estimates the amount of bias.

Note that the predictions of auction theory only depend on the signs of the comparative statics. Even if V_t and SD_t were biased measures of v_t and $\sigma_{x|v,t}$, as long as the measures are correlated with the true values, the signs on the results in Column 1 are still valid. Analysis of survey results in Yin (2002) suggests that V_t and SD_t are correlated with v_t and $\sigma_{x|v,t}$.

3.1 Correcting for potential bias in V_t and SD_t

V_t and SD_t are potentially biased measures of v_t and $\sigma_{x|v,t}$. I model and estimate the potential bias as follows. I treat the responses $X_{i,t}$ from my survey respondents as potentially biased draws of signals $x_{i,t}$ that the auction participants draw about v_t. Thus, $X_{i,t}$ are drawn from a potentially different distribution than the one that the auction participants face. I model the responses from my inexperienced respondents, denoted $X_{a,i,t}$, as draws from a distribution whose mean may differ from v_t by a shift factor γ_0 and a scale factor γ_1 and whose variance may be different as well: $X_{a,i,t} \backsim (\gamma_0 + \gamma_1 v_t, \sigma^2_{x|v,a,t})$. I assume that the experienced survey respondents are more similar to the auction participants. I model their responses as being drawn from a distribution whose mean only differs from v_t by a shift factor θ_0 and whose variance may be different: $X_{e,i,t} \backsim (\theta_0 + v_t, \sigma^2_{x|v,e,t})$. An unbiased estimate of v_t can then be written as

$$\hat{v}_t = \frac{J_{e,t}}{J_t}(V_{e,t} - \theta_0) + \frac{J_{a,t}}{J_t}\left(\frac{V_{a,t} - \gamma_0}{\gamma_1}\right), \tag{3}$$

where $J_{e,t}$ is the number of experienced survey responses in each auction, $J_{a,t}$ is the number of inexperienced survey responses in each auction, and J_t is the total number of survey responses to each auction. The parameters to be estimated are θ_0, γ_0, and γ_1. They capture the amount of bias in the responses.

I employ the same process to model the potential bias in SD_t as a measure of $\sigma_{x|v,t}$. I assume that my experienced respondents draw from a distribution with variance $\sigma^2_{x|v,e,t} = \eta_0 + \sigma^2_{x|v,t}$, whereas my inexperienced respondents draw from a distribution with variance $\sigma^2_{x|v,a,t} = \delta_0 + \delta_1 \sigma^2_{x|v,t}$. The resulting unbiased estimate of the information dispersion faced by the auction participants is as follows:

$$\hat{\sigma}_{x|v,t} = \sqrt{\frac{J_{e,t}}{J_t}(SD^2_{e,t} - \eta_0) + \frac{J_{a,t}}{J_t}\left(\frac{SD^2_{a,t} - \delta_0}{\delta_1}\right)}. \tag{4}$$

The parameters to be estimated are η_0, δ_0, and δ_1. They capture the amount of bias in the dispersion of responses.

I can use a moment condition to identify θ_0, γ_0, and γ_1. I set the standard deviation of the experienced survey responses equal to the definition of the sample standard deviation, replacing $V_{e,t}$ with $\hat{v}_t + \theta_0$. The following moment condition is then estimated simultaneously with a price equation that includes $\hat{v}_t$ as a regressor:

$$SD_{e,t} = \sqrt{\frac{\sum^{J_{e,t}}(X_{e,i,t} - (\hat{v}_t + \theta_0))^2}{J_{e,t} - 1}}. \tag{5}$$

Column 2 presents the results of simultaneously estimating the price equation and the moment condition in Equation 5. I remove the constant from the price equation since θ_0 and γ_0 now serve to estimate the intercept. I now estimate v_t and $\sigma_{x|v,t}$ in the price equation by $\hat{v}_t$ and $\hat{\sigma}_{x|v,t}$, respectively.

Overall, we get the same signs and magnitudes as for the corresponding coefficients in Column 1. These results confirm the Nash CV model as appropriate to describe my sample of auctions and confirm my hypothesis about the credibility of information.

The scale parameters on $V_{a,t}$ and $SD^2_{a,t}$ are both positive ($\gamma_1 = 1.03$, $\delta_1 = 1.83$), confirming that the inexperienced responses are correlated with the experienced responses, which I assume to be perfectly correlated with the signals drawn by the auction participants. As expected, the coefficient on $\hat{v}_t$ is equal to 1 and significant. Since the coefficient on V_t in Column 1 was already equal to 1, this seems to indicate that there was not much need for bias correction of the survey measure. Indeed, the estimate of the scale bias in $V_{a,t}$ of 1.03 indicates that even the inexperienced responses are able to capture relative values of items. The inexperienced respondents tend to overestimate the value of the items by \$83.61. Just as one would expect from more knowledgeable survey respondents, the experienced respondents are closer to v_t and overestimate by only \$27.04.

The variance for the inexperienced respondents tends to be twice as large in scale and shifted upwards compared to $\sigma^2_{x|v,t}$. Translating this into standard deviation terms, $SD_{a,t}$ is approximately 1.35 ($= \sqrt{1.83}$) times larger than $\sigma_{x|v,t}$ and overestimates $\sigma_{x|v,t}$ by 276.37 ($= \sqrt{76381.0}$). Since inexperienced respondents might not understand all the details of the auction description, we would expect that the amount of information they would gather from those descriptions would be less than what auction participants would acquire. A bit surprising is the finding that experienced respondents underestimate $\sigma_{x|v,t}$ by 245.40 ($= \sqrt{60222.6}$). This is consistent with the concept that those who have participated in eBay auctions have learned how to better interpret auction descriptions because of their experience. It suggests that my experienced survey respondents may be even more experienced than the average participant in my sample of auctions. Despite these differences, the magnitude of the coefficients on $\hat{\sigma}_{x|v,t}$, $\hat{\sigma}^2_{x|v,t}$, and $\hat{\sigma}_{x|v,t} \times N_t$ are not that different from their counterparts in Column 1. For the purposes of estimating changes in price with respect to dispersion, SD_t seems to work sufficiently well despite biases.

3.2 Instrumental Variables Estimation

I present an alternative empirical specification in Column 3 of Table 4 that addresses the potential endogeneity and measurement error from using N_t as a measure of the number of participants in the auction. I consider these results to be a robustness check on the previous section. The endogeneity and errors may not have generated severe bias in Columns 1 and 2, so employing potentially weak instruments may not yield more accurate estimates.

Much of the empirical work on auctions faces the problem of an endogenous number of bidders. The auction participants who chose to bid may have been attracted by some aspect of the item being auctioned that is not captured in the other regressors or is unobservable to the econometrician. If this aspect is correlated with price, then we need to instrument for the number of bidders. One of the advantages of a survey measure of v_t is that survey readers will tend to pick up the same idiosyncratic aspects of items that affect a participant's valuation in an auction. Thus, $\hat{v}_t$ controls for the omitted item characteristics that usually cause the error term in the price equation to be correlated with N_t. However, if the actual participants in eBay computer auctions are better equipped than my survey respondents to spot a good deal on eBay, then N_t may still be correlated with unobservable determinants of price.

The number of bidders observed in the auction may not equal the number of participants who drew signals about the auctioned item's value. We will not observe bids from auction participants arriving late to the auction who draw a signal about the value, but find that the price has already been bid above their valuation.[18] In addition, "bottom feeders" on eBay may submit extremely low bids on the off chance that no one else enters the auction. These bidders may not be taken seriously as a participant who is drawing a signal about the valuation of the item. It is possible that the net effect of these sources of measurement error is negligible, in which case instrumenting may be worse than using N_t directly.

To produce the estimates in Column 3, I again simulataneously estimate the price equation as modeled in Column 2 and the moment condition. However, I treat N_t as endogenous and instrument for N_t. I use the conventional instruments that determine access to the auction (e.g., length of auction, time of auction) as well as some instruments unique to eBay and my survey data. While these instruments are uncorrelated by construction with the error term in the price equation, they are fairly weak instruments since they are not highly correlated with N_t. Summary statistics of instruments for N_t are presented in Appendix B, Table 8.

The weakness of the instruments is reflected in numerous insignificant coefficients in Column 3. Nevertheless, we get the same signs as in Columns 1 and 2, with the exception of the statistically insignificant sign on $NEG_t \times \hat{\sigma}_{x|v,t}$. The magnitudes are essentially the same for corresponding coefficients across all three columns, with the exception of the statistically insignificant coefficient on N_t and statistically insignificant estimates of some of the bias

[18] The number of auction participants who draw signals is the important factor for evaluating the winner's curse, not the number of bidders, since the winner uses this information to determine how much higher than v_t her signal might be if her signal was the highest among all those draws.

parameters (η_0, δ_0, and θ_0). After correcting for potential endogeneity and measurement error from using N_t as a measure of n, the conclusions of Column 1 remain. Prices are declining with the number of bidders and dispersion of information, indicative of Nash CV behavior.

3.3 Modeling $\mu_{v,t}$

In my specifications thus far, I assumed that all bidders faced a common μ_v over all auctions. However, a bidder may be in the market for a certain brand or speed of computer, so she may search eBay for computers that match those criteria. This means that the bidder will only view and draw signals from a selected number of auctions. It is likely that these criteria will cause the bidder to draw from a different μ_v than a bidder who searches by a different set of criteria. To check the restrictiveness of this assumption, I modified the specification for the price equation to include $\mu_{v,t}$ separately from $\hat{v}_t$ and examine whether estimates were significantly different from just using $\hat{v}_t$ alone. Results are presented in Column 4 of Table 4.

First, I constructed a set of regressors describing the technical specifications of computers that could be plausible search criteria. These regressors are described in detail in Appendix C. I then constructed an equation that regressed $\hat{v}_t$ on those regressors. I designated the fitted value from this regression as an estimate of $\mu_{v,t}$ for each auction. I added this fitted value as a regressor to the price equation. I then used $\hat{v}_t$ as my measure of v_t. I simultaneously estimated the price equation, moment condition, and the $\mu_{v,t}$ equation. I again used N_t as a measure of n_t and $\hat{\sigma}_{x|v,t}$ as a measure of $\sigma_{x|v,t}$.

The coefficient on $\mu_{v,t}$, while statistically significant, is relatively small (0.11) compared to that on $\hat{v}_t$ (1.96). This seems to indicate that the assumption of common μ_v across all auctions does not significantly change estimates. The use of $\hat{v}_t$ to control for detailed product variation across auctions has a larger influence on price than any differential effect that product categories might have on price. Again, all the signs and magnitudes are approximately the same as in Columns 1 and 2, except for some of the survey bias parameters (γ_0, γ_1, and η_0) and the coefficient on $\hat{v}_t$. However, the estimate of γ_1 and coefficient on $\hat{v}_t$ are approximately equal (2.39 and 1.96, respectively), so they roughly cancel each other out when substituted back into the price equation. It is not surprising that these results are twice the size of the corresponding values in the other columns. We essentially include $\mu_{v,t}$ twice in the equation: once as a regressor, and once as part of $\hat{v}_t$. A joint F-test of the significance of employing $\mu_{v,t}$ and $\hat{v}_t - \mu_{v,t}$ instead of $\hat{v}_t$ failed. To arrive at the partial effect of $\hat{v}_t$ on price, we should divide its coefficient in half ($= 0.98$). The resulting effect on price from v_t is thus equivalent across all columns. Likewise, we should then divide the parameter γ_1 in half to get the effect of $V_{a,t}$ on price ($= 1.19$).

All approaches confirm that the data in eBay online auctions for computers is consistent with Nash CV auctions. Prices fall with dispersion at a decreasing rate. Prices also fall with the number of bidders in this sample of auctions. Reputation determines the credibility of information dispersion: higher reputations cause prices to rise more when information is less dispersed and fall more when information is more dispersed.

4 Analysis

Thus far, tests of Nash equilibrium behavior have been based on comparative static signs. In this section, I rely on magnitudes of estimated coefficients and introduce assumptions about the shape of the distribution of common values and information signals in order to determine the actual difference between theoretically predicted prices and eBay prices. I also rely on magnitudes to estimate the potential winner's curse in these markets and compare the price effects of reputation, information dispersion, and the credibility of information. I use the coefficients from Column 2 of Table 4 for my analysis.

Table 4: Simultaneous equation estimates of price equation

Parameter	Column 1	Column 2	Column 3	Column 4
θ_0		27.039‡	1.772	289.748‡
		(0.407)	(156.267)	(0.544)
γ_0		83.611‡	60.405	-76.906‡
		(0.397)	(162.560)	(1.289)
γ_1		1.033‡	1.029‡	2.392‡
		(2.72E-04)	(0.050)	(1.015E-03)
η_0		-60222.6‡	-9259.78	78034.3‡
		(803.752)	(302009)	(997.537)
δ_0		76381.0‡	58047.6	5247.51‡
		(268.241)	(1557071)	(397.027)
δ_1		1.83103‡	2.488	1.396‡
		(7.64E-03)	(1.760)	(7.57E-03)
Variable				
Constant	69.301			
	(120.627)			
$\hat{\text{v}}_t$	1.046‡	1.086‡	1.172‡	1.960‡
	(0.059)	(3.85E-04)	(0.104)	(7.63E-04)
$\hat{\sigma}_{x\|v,t}$	-1.483‡	-1.48479‡	-1.448‡	-1.446‡
	(0.450)	(3.45E-03)	(0.692)	(5.50E-03)
$\hat{\sigma}^2_{x\|v,t}$	1.20E-03‡	1.73E-03‡	1.79E-03	0.16E-02‡
	(4.26E-04)	(7.07E-06)	(1.20E-03)	(-8.85E-06)
N_t	-11.811	-9.120‡	-21.819	-8.423‡
	(11.145)	(0.047)	(23.900)	(0.053)
$\text{N}_t \times \hat{\sigma}_{x\|v,t}$	0.021	0.024‡	0.012	0.018‡
	(0.022)	(1.35E-04)	(0.059)	(1.31E-04)
$\text{SCORE}_t \times \hat{\sigma}_{x\|v,t}$	-1.16E-04†	-1.38E-04‡	-7.05E-05	-1.29E-04
	(6.68E-05)	(4.78E-07)	(4.82E-04)	(4.97E-07)
$\text{NEG}_t \times \hat{\sigma}_{x\|v,t}$	1.39E-03	1.52E-03‡	-6.56E-04	1.41E-03‡
	(1.73E-03)	(1.05E-05)	(0.015)	(1.08E-05)
SCORE_t	0.091‡	0.079‡	0.079	0.086‡
	(0.038)	(1.66E-04)	(0.125)	(1.96E-04)
NEG_t	-0.901	-0.731‡	-0.281	-0.780‡
	(0.816)	(3.39E-03)	(4.202)	(4.08E-03)
SCORE_t^2	-1.12E-06	-1.10E-06	-2.13E-06	-1.24E-06
	(1.15E-06)	(5.76E-09)	(3.03E-06)	(5.79E-9)
$\mu_{v,t}$				0.114‡
				(1.69E-03)
R^2	0.72	0.72	0.69	0.71

‡significant at 5 percent, †significant at 10 percent.

4.1 Differences between Nash CV & eBay prices

The price equation estimated in Section 3 is an approximation to the true price function. The functional form chosen for p did not impose any particular auction model; the comparative statics identified the Nash CV model as appropriate to describe eBay computer auction prices. Thus, the estimated parameters and coefficients in Table 4 are free of any assumptions about bidder behavior or CV versus PV. To quantify how close eBay prices are to Nash CV prices as predicted by auction theory, I simulated Nash CV prices based on the n_t, v_t and $\sigma_{x|v,t}$ I had estimated for the eBay prices.

I employed the estimated survey bias parameters from Column 2 by plugging them back into $\hat{v}_t$ and $\hat{\sigma}_{x|v,t}$ to generate a $\tilde{v}_t$ and $\tilde{\sigma}_{x|v,t}$ for each auction. I then calculated the mean and standard deviation of $\tilde{v}_t$ and treated these as estimates of the common μ_v and σ_v over all t auctions. I tried several measures for n_t, including the first stage fitted value from instrumental variables and $N_t \pm 20$ percent, ± 50 percent, and $+100$ percent. There was not much difference in the resulting simulated Nash CV prices, so I present the results from simply using N_t as a measure of n_t.

I drew the second highest signal out of N_t draws made from a lognormal distribution with mean $\tilde{v}_t$ and standard deviation $\tilde{\sigma}_{x|v,t}$.[19] I generated the Nash CV price for each auction using these values and a numerical approximation to the theoretical Nash CV price (see Appendix D).[20] I repeated this process 1000 times for each auction. The average over these prices is the simulated Nash CV price for auction t. I then adjusted the expected price for reputation effects and interaction effects between reputation and dispersion based on the estimates from Column 2 of Table 4. Simulated naïve CV prices were generated by taking the average over the draws of the second highest signal and then adjusting for reputation effects.

Figure 2 plots simulated prices based on lognormally distributed signals and actual prices

[19] I also simulated prices for normal distributions, but the shape of those distributions did not fit the eBay price data as well. The lognormal and normal distributions most closely matched the observed distribution of survey responses.

[20] The Gauss-Hermite quadrature method is outlined in Judd (1998). I corrected for an error in the translation presented in the text for lognormally distributed signals.

from eBay for each auction in my sample. Along the horizontal axis, auctions are presented in increasing order by the simulated Nash CV prices. Simulated prices are plotted as diamonds, while the associated eBay price is plotted as circles.

The scatterplot shows that eBay prices track the slope and curvature of the Nash CV simulated prices very closely. eBay prices tend to be lower than the Nash CV predictions by about 35 percent. Figure 2 confirms that eBay prices react to changes in N_t and $\hat{\sigma}_{x|v,t}$ in the manner predicted by Nash CV, although prices may not exactly replicate the magnitudes of those changes.

The difference between the simulated and actual prices suggests that bidders may be over-reacting to the winner's curse. Alternatively, information contained in auctions outside of my sample or information passed between the seller and auction participants that is not posted in the auction description may be affecting auction participants' estimates of v_t. The estimates in the previous section do not take into account the effects of multi-auction behavior or of private information revelation, which would affect the magnitude of the estimates, but not the sign. Kremer & Jackson (2004) establish that as $n \rightarrow \infty$, prices may converge to values less than the common value in multi-unit discriminatory auctions. If eBay bidders participate in multiple auctions over time and adjust bids so that they only win in one auction, their behavior might resemble that of multi-unit discriminatory auctions. Away from the limit, this behavior might result in prices that are consistently lower than simulated Nash CV prices.

4.2 Winner's Curse

If the difference between prices from naïve bidding behavior and the value of the auctioned items are not that large, then it may not matter if auction participants play Nash CV strategies. How much is really at risk if participants do not account for the winner's curse? We can answer this question by considering the prices the winning bidder would have paid if auction participants had employed naïve CV bidding behavior. We can also examine the

Figure 2: eBay prices vs. simulated Nash CV prices
The theoretical Nash CV price is simulated for each auction. Auctions are ordered by simulated prices along the horizontal axis. The simulated prices as well as the eBay prices in each auction are plotted along the vertical axis. eBay prices are highly correlated with simulated Nash CV prices.

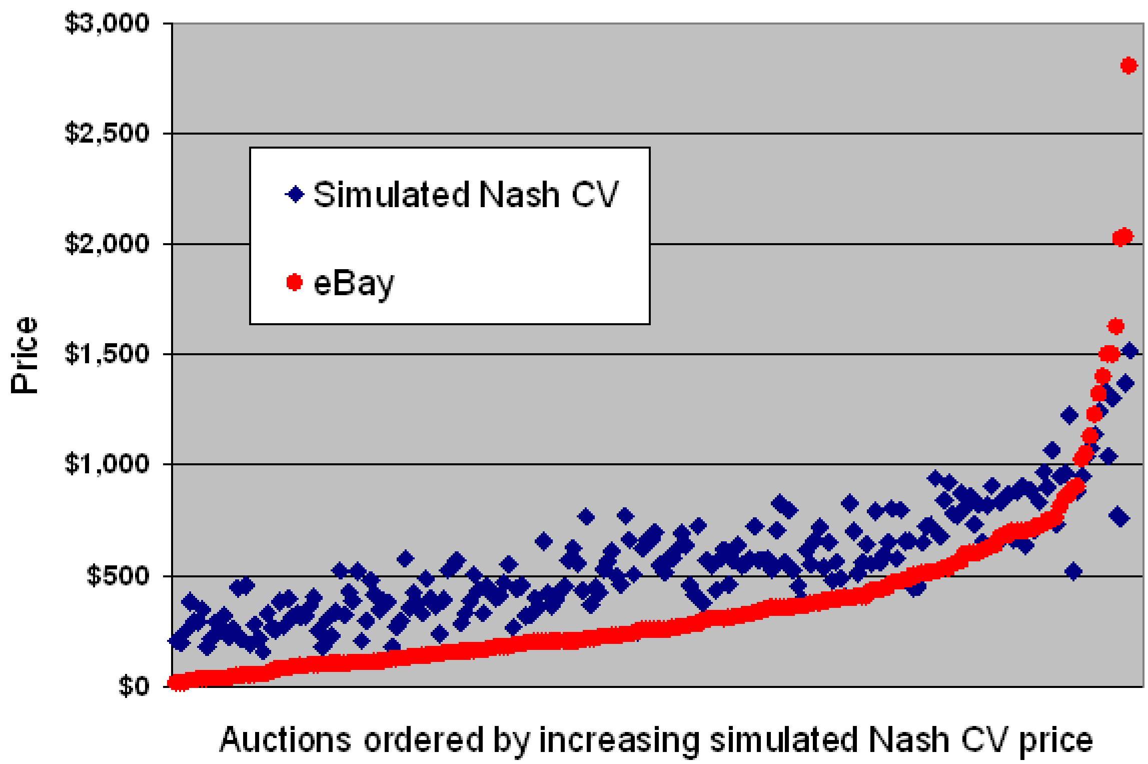


Table 5: Potential winner's curse

Prices	**average**	**diff. w/ naïve**	**diff. w/ $\tilde{v}_t$**
simulated Nash CV	\$557.19	-\$191.29	-\$21.42
simulated naïve CV	\$748.48	0	\$169.87
eBay	\$361.02	-\$387.46	-\$217.59

difference in prices if auction participants ignored changes in the number of participants, dispersion, and their interaction effects.

The first column of numbers in Table 5 reports the summary statistics over all auctions for the simulated Nash CV prices, simulated naïve CV prices, and eBay prices. The average difference between simulated naïve CV prices and the simulated Nash CV and eBay prices are presented in the middle column of numbers. The last column presents the difference between the estimated common value of the items and the simulated Nash CV, simulated naïve CV, and eBay prices.

eBay winners pay a lot less for their items than they would if they had behaved naïvely: naïve CV prices are 34 percent higher than Nash CV prices, and more than double eBay prices. The winner's curse would be \$169.87 on average, since naïve auction winners would have paid that much more over the value of the item. Instead, the consumer surplus in these auctions is \$217.59 on average.[21] However, as suggested in the previous section, it is likely that the eBay bidders over-react to the winner's curse, and therefore bid less than predicted by Nash CV. The average consumer surplus that would be predicted by Nash CV is \$21.42.

I further decompose the effects of naïve bidding into the loss from ignoring changes in information dispersion and the loss from ignoring changes in the number of auction participants. For each auction, I consider three scenarios: an increase in information dispersion by 1 unit, an increase in the number of auction participants by 1 person, and both changes. The columns of Table 6 present the results from each scenario. I then calculate how much

[21] eBay winners paid more than $\tilde{v}_t$ in less than 5 percent of the auctions in my sample. These auctions were characterized by higher than average $\tilde{v}_t$, $\tilde{\sigma}_{x|v,t}$, $SCORE_t$, and NEG_t.

Table 6: Price effects of naïve behavior

Behavior	Price change from		
	incr. $\sigma_{x\|v,t}$ by 1	incr. n_t by 1	both
Nash CV	-\$0.30	-\$1.63	-\$1.05
ignore $\sigma_{x\|v,t}$	0	-\$9.12	-\$9.12
ignore n_t	-\$0.46	0	-\$0.46
naïve CV	0	0	0

prices would change under the Nash CV model based on the estimates in Column 2, Table 4. I report those results in the first row. I also calculate how much the price would change if auction participants were naïve with regard to dispersion, naïve with regard to the number of auction participants, or both. Those calculations are made by setting the coefficients on dispersion, the number of auction participants, and interaction terms in Column 2 of Table 4 to 0, respectively. The results for each of those models of bidding behavior are presented in the remaining rows of Table 6.

Comparing the first two rows in Column 1, we can see that if all auction participants ignored the effect of a 1 unit increase in dispersion, prices would be \$0.30 higher than Nash prices. If all auction participants ignored n_t but not the increase in dispersion, then they would not take into account the interaction effect between n_t and $\sigma_{x|v,t}$. Prices would be \$0.16 (=\$0.46-\$0.30) lower than Nash prices. A bidder who did not ignore changes in n_t could thus profitably win against the other bidders in this auction by bidding any amount between the Nash CV price and Nash CV price minus \$0.16.

The second column of numbers shows price changes under each model when an additional auction participant enters the auction. Failure to account for that participant leads to prices \$1.63 higher than Nash prices. The failure to account for the interaction effect between n_t and $\sigma_{x|v,t}$ will result in prices \$7.49 (=\$9.12-\$1.63) lower than Nash prices.

The last column of numbers presents price changes if both dispersion and the number of auction participants increase. Ignoring the number of auction participants alone will lead to prices \$0.59 higher (=\$0.46-\$1.05) than Nash. Ignoring dispersion alone will lead to prices \$8.07 (=\$9.12-\$1.05) below Nash.

To place these counterfactual scenarios in context, consider an auction from my sample whose item description generated a level of information dispersion in the top quartile of my sample, $\tilde{\sigma}_{x|v,t} = 420.46$ and attracted less than the average number of auction participants in the sample, $N_t = 3$. The winning price was \$137.50 for this item. Holding all else equal, if the auction participants had ignored the fact that this auction attracted 3 auction participants and simply assumed that the number of auction participants equaled the average N_t in my sample of 6, then the winning bidder would have overpaid by \$2.47. Holding all else equal, if the auction participants had ignored the fact that dispersion was 103.96 higher than the average in my sample, and simply acted as if dispersion was 316.64, then the winning bidder would have overpaid by \$18.30. If the auction participants had ignored both of these facts, then the winning bidder would have overpaid by \$17.62

In this sample of auctions, the declining prices as n_t rises are countered by the interaction effect with dispersion. By appropriately accounting for changes in the number of auction participants and dispersion, bidders avoid paying more than is necessary (i.e., more than the Nash equilibrium price) to win in some auctions, or they avoid losing the auction at a price less than the predicted Nash price.

4.3 Information Dispersion, Reputation, and Credibility

What do these estimates mean for seller strategies on eBay? Table 7 examines how prices will change with dispersion and reputation.

A seller who invests in acquiring and publishing more information in the auction description to reduce dispersion will earn a return that depends on her reputation and current level of information dispersion. The return from decreasing dispersion by 1 unit is \$0.23; for the average seller, the credibility in the reduction of dispersion due to their reputation adds another \$0.11 to the price. The \$0.08 premium from increasing reputation by 1 unit is mitigated

Table 7: Price effects of credibility

Partial effect	Price change from		
	decr. $\sigma_{x\|v,t}$ **by 1**	**incr.** $SCORE_t$ **by 1**	**both**
$\frac{\partial p_t}{\partial SCORE_t}$*	-	\$0.08	\$0.08
$\frac{\partial p_t}{\partial \sigma_{x\|v,t}}$*	\$0.23	-	\$0.23
$\frac{\partial^2 p_t}{\partial \sigma_{x\|v,t} \partial SCORE_t}$	\$0.11	-\$0.04	\$0.06
Total effect	\$0.34	\$0.04	\$0.38

*These partial effects exclude the interaction effects with respect to reputation.

by the -\$0.04 interaction effect with dispersion. A better reputation increases credibility, and therefore increases the penalty on price for having high information dispersion.

Direct comparisons of the importance of these effects is difficult, since the units are not the same. To place these counterfactual changes in context, consider a seller from my sample who had no reputation ($SCORE_t$ and NEG_t both equal 0) and posted an item description that generated the median level of information dispersion among all the samples in my auction, $\tilde{\sigma}_{x|v,t} = 321.50$. The seller in this case sold the item for \$255.07. If the seller had the median reputation, $SCORE_t = 68$, then holding all else equal, she would have sold the item for \$5.36 more. If the seller instead had posted an item description that generated a level of information dispersion equivalent to the levels of those posting in the lowest quartile of $\tilde{\sigma}_{x|v,t}$, $\tilde{\sigma}_{x|v,t} = 218.51$, then holding all else equal, she would have sold the item for \$46.79 more. Based on these estimated price effects, uncertainty about the value of a good due to information dispersion over auction participants seems to be a more important source of uncertainty than information asymmetry between the buyer and the seller.. If both the seller's reputation had increased and dispersion had decreased, the seller would have sold the item for \$50.16 more.

Empirical analysis of eBay auction prices which ignores the breakdown of the direct effect from reputation and the interaction effect of reputation may lead to the conclusion that reputation has a negligible effect on price. Because of this interaction effect, a seller has an incentive to both decrease dispersion and increase her reputation, reducing uncertainty about the value of computers in eBay markets.

5 Conclusion

The results in this paper are unattainable without employing theory, econometric modeling, and external survey data. From auction theory, I derive implications of different auction models when information dispersion and the number of bidders are observable with error. These implications permit joint testing of the information structure (CV or PV) and bidding behavior (Nash or naïve strategies) in these auctions.

To measure information dispersion and unobservable item values, market data is augmented by survey data. By harnessing the dispersion of information in the non-eBay market, I am able to generate a measure that is independent of bidding data. Although dispersion could be derived from knowledge of all the bids in an auction or knowledge of some bids and the true common value, one would have to assume a PV or CV setting to test for Nash bidding behavior or assume Nash bidding behavior to identify the information structure. The highest bid is not observed in the eBay data, and ex-post valuations for the goods are not readily available. The survey data provides extra identification power to 1) simultaneously distinguish between CV and PV without imposing Nash equilibrium bidding behavior, distinguish between Nash and naïve bidding behavior without assuming a PV or CV setting, employ only price data from the auctions as opposed to all bids, and estimate any potential bias between my measures of dispersion and the true common value and dispersion of information. My estimates indicate that eBay auctions for computers are best described as CV auctions where prices reflect Nash equilibrium bidding behavior. They also indicate that my survey measures provide reasonably accurate approximations for the true values.

The survey data also permits treatment of information about the item being sold as distinct from information about the seller. I identify two different effects of reputation: the mean shift that a reputation premium may have on the expected common value and the credibility reputation lends to changes in the dispersion of information in an auction. The estimates indicate that uncertainty about the value of a good due to information dispersion over auction participants seems to be a more important source of uncertainty than information asymmetry between the buyer and the seller. Empirical analysis of eBay auction prices which ignores the effect of information dispersion on price may inadvertently conclude that reputation has a negligible effect on price, but both are important. Sellers with a good feedback score have an incentive to provide precise descriptions, since they benefit from the complementarity between reputation and product information.

I adjust for potential bias in my survey measures and quantify the potential winner's curse in this market. Auction participants on eBay account for the winner's curse, paying less than the common value on average. Rough calculations of naïve bidding models indicate that there is potential for a large winner's curse. Even in the pedestrian market of online computer auctions, prices exhibit the equilibrium behavior predicted by sophisticated bidding strategies.

A Survey Description

Auction descriptions were edited to remove all bids and identities (other than seller identification within the auction description itself) and reputations involved. A CGI script was developed by Paul Hartke to translate PostScript graphics of these auctions into web-viewable formats, and automate a process to assign unique ID numbers to survey respondents and record which auctions were viewed and respondents' values. A separate Formage script was written to solicit background information on the respondents. The following solicitation was sent to friends of the author and posted to relevant newsgroups:

"Could you please help my friend Pai-Ling Yin, http://www.stanford.edu/~pyin, in her PhD economics research project to determine the distribution of commonly held values for products? Just fill out a short survey asking you to look at the descriptions of 10 computers and giving your estimate of how much they are worth. Even if you are not familiar with computers and their prices, your best guess will still be useful to Pai. So send this on to your grandparents, parents, siblings, cousins, friends, and co-workers for extra chances at winning!

"All completed surveys will be entered in a drawing for two $1,000.00 prizes and thirty $60 prizes. For each friend you get to do the survey, you get an extra chance to win. Deadline for all submissions is 11:59pm, July 20, 2002. E-mail pyin@stanford.edu if you can't make the deadline but still want to participate.

"Thanks very much! Email pyin@stanford.edu if you have questions. Privacy will be honored; no names or emails will be released except for the winners (posted at the survey site after 1/1/03)."

PRIZE DETAILS:

"As a reward for participating, a drawing will take place on January 1, 2003, over all completed surveys and referrals. Two people will win checks for $1,000.00. Odds of winning depend on the number of times you participate and the total number of surveys completed.

"As an incentive to think sincerely about your estimates, fifteen $60.00 prizes will be awarded to the people whose estimates are closest to the average of all other estimates in the same auction, and fifteen $60 prizes will be awarded to the people whose estimates are closest to a set of estimates provided by a panel of computer sales people. This allows both computer experts and non-experts to have a chance at winning."

BACKGROUND:

1. Please enter your e-mail address. This will be used only to contact you if you win. Please use the same e-mail if you participate more than once.

   Did someone refer you to this survey? Please enter his/her e-mail address:

2. Are you involved in work or hobbies that cause you to be very familiar with the prices of computers and computer components? YES/NO

3. Have you been shopping for a computer in the last 6 months? YES/NO

4. How many computers have you bought in the past 6 months (either for personal use or for work)? 0/1/2+

   If you bought a computer, did you buy it/them through (check all that apply):

   an auction process (does not include using "Buy It Now")?

   a retailer (includes using "Buy It Now" to buy the computer at a set price rather than at the winning auction price)?

   a wholesaler (someone who normally sells computers to stores, not directly to consumers)?

5. Have you ever looked at computers on an online auction website? YES/NO

   On eBay? YES/NO

6. In how many online computer auctions have you participated in your life?

   0/1/2-5/6+

How many were on eBay? NONE/SOME/ALL

How many of the computer auctions did you win? NONE/SOME/ALL

"After you hit the submit button, you will be given descriptions to evaluate, one at a time. You will be given 1 chance to win prizes for every 10 auctions you complete.

"You may want to copy your answers for each auction on some paper so that you can compare auctions.

"You can use the 'Back' and 'Forward buttons on your browser to compare descriptions; if you want to change answers, you can use the back button as well, but make sure to click "Send" to register the change. Then click 'Send' on the subsequent pages to return to the auction you left off with.

"Send e-mail to pyin@stanford.edu if you have any problems, want to change an answer after exiting, or want to confirm your entries. Please make sure the above answers are correct before you click 'Send', so that you don't have to backtrack to this page to change any answers.

"Please wait a few seconds while the computer description loads...

"Assume that your friend is interested in buying the computer described below. Taking into account all information that you see (including shipping and insurance costs), what is the MOST she should be willing to pay for this computer (NOT how much she should bid!)? Even if you don't understand some of the description, please do your best to be consistent (better computers cost more). Feel free to look at ads or websites to help you make better recommendations, but please DO NOT look at online auction sites to get a sense of prices. Scroll ALL the way down to enter your value at the bottom of the description."

B Instruments for N_t

Instruments should be correlated with the number of bidders, but, conditional on other covariates (in particular, the mean of the survey responses), not correlated with unobservable

Table 8: Summary statistics for bidder instruments

Variable (222 auctions)	**mean**	**st. dev.**	**min**	**max**
webcounter hits $HITS_t$	249.67	167	38	1215
webcounter dummy $NOHITS_t$	0.33	-	0	1
minimum bid $MINBID_t$	58.25	112.95	0.01	650.00
auction end time $ENDHOUR_t$	15	5	1	24
auction end day $ENDDAY_t$	4	2	1	7
auction duration $LENGTH_t$	3.45	1.1	1.5	7
item listed by photo $GALLERY_t$	0.33	-	0	1
item at top of list $FEATURE_t$	0.16	-	0	1
N_t from similar auctions $ALTN_t$	6.60	1.85	3	11.8

determinants of price.

Many sellers utilize "webcounter" software to track the number of times their auctions were accessed by a web browser. This number was designated as $COUNTER_t$. It is an upper bound on the number of participants active in that auction, since it includes repeat site access by the same user. A signal of the item's value cannot be drawn before viewing the auction website. Therefore, $COUNTER_t$ is uncorrelated with the value of the item being auctioned. For those auctions without counters, the average of $COUNTER_t$ across all auctions is used.

Different ending times of the auction, $HOUREND_t$ and $ENDDAY_t$, and the length of the auction in days, $LENGTH_t$, will change the potential number of participants in the auction but are unlikely to be correlated with the value of the item. $GALLERY_t$ and $FEATURE_t$ indicate whether an item was included in the photo gallery or listed at the top of the webpage listings. These characteristics should influence the number of people that enter the auction by changing the item's visibility.

I assume that changing the minimum bid, $MINBID_t$, only affects price by changing the number of participants entering the auction. Anecdotal evidence suggests that sellers

Table 9: Summary statistics for regressors for a priori value

Variable (222 auctions)	mean	st. dev.	min	max
recognizable computer $BRAND_t$	0.27	-	0	1
quality of brand of $PROCESSOR_t$	2.14	1.11	0	3
processor $SPEED_t$	1088	684.88	0	2530
RAM_t memory capacity	210.77	196.04	0	1100
$HARDDRIVE_t$ memory capacity	27724	27755	0	160000
device for $INTERNET_t$ access	1.31	0.83	0	2
includes $MONITOR_t$	0.21	-	0	1
includes CD_t or DVD drive	0.83	-	0	1
includes $FLOPPY_t$ drive	0.66	-	0	1

like to generate interest in their auctions by lowering starting bids, so it is not necessarily a reflection of the value of the item.

$OTHERN_t$ is an instrument that is independent of any seller actions. It is the average number of bidders observed participating in the ten other auctions which received the closest $V_{e,t}$. This instrument should be correlated with the number of participants in the market for computers of equivalent value to the one listed in auction t without being correlated with any specific product characteristic of the computer in auction t.

C Regressors for $\mu_{v,t}$

I constructed a set of hedonic characteristics of the computers to be used as regressors for determining $\mu_{v,t}$. The expected value of a computer satisfying certain criteria before a bidder has seen the auction description is captured in $\mu_{v,t}$, while v_t measures the value of a computer after having seen the auction description. Summary statistics are presented in Table 9.

The dummy variable $BRAND_t$ indicates whether the computer had a recognizable brand name (Toshiba, Dell, Hewlett-Packard, IBM, Compaq) or not. A ranking of the processor brands in $PROCESSOR_t$ ranged from no mention of processor brand (= 0) to Pentium (= 3). The processor's speed was denoted as $SPEED_t$. The amount of memory included was characterized by the ram and harddrive capacity ($RAM_t, HARDDRIVE_t$). I ranked the presence of a communications device in $INTERNET_t$ (0 for no device, 1 for modem, 2 for other). Dummies were created for whether a monitor, cd/dvd drive, and floppy drive was included or not ($MONITOR_t, CD_t, FLOPPY_t$). If the auction description did not provide any information about a characteristic, the value was coded as 0.

D Analytical derivation of $E[p]$

The bid function in Equation 1 can be written explicitly as

$$(6) \qquad b(x_i) = \frac{\int_{\underline{v}}^{\overline{v}} v f_x^2(x_i|v) F_x^{n-2}(x_i|v) f_v(v) dv}{\int_{\underline{v}}^{\overline{v}} f_x^2(x_i|v) F_x^{n-2}(x_i|v) f_v(v) dv}, \text{ (Milgrom \& Weber,1982)}$$

where $F_x(x_i|v)$ is the cumulative distribution of x. To derive the expected value of the 2nd highest bid, one would have to solve for

$$\Pr[b(x_i) \leq v] = \Pr[x_i \leq b^{-1}(v)] = F_x(b^{-1}(v))$$

with associated density

$$f_x(b^{-1}(v)) \frac{1}{b'(v)},$$

where

$$b'(v) = \frac{\partial b(v)}{\partial v},$$

and solve for the 2nd order distribution of

$$f_x^{(n-1)}(b^{-1}(v)) \frac{1}{b'(v)} = n(n-1) F_x(b^{-1}(v))^{n-2} f_x(b^{-1}(v)) \frac{1}{b'(v)} [1 - F_x(b^{-1}(v))],$$

and then integrate to get

$$\int_{-\infty}^{\infty} x_i(n-1)F_x(b^{-1}(v))^{n-2}f_x(b^{-1}(v))\frac{1}{b'(v)}dx.$$

I numerically approximate this expression in order to generate Nash CV prices.

References

Akerlof, George A., "The Market for 'Lemons': Quality Uncertainty and the Market Mechanism," *Quarterly Journal of Economics*, 1970, *84*, 488–500.

Anand, Bharat N. and Ron Shachar, "Advertising, the Matchmaker," 2004. working paper.

___ **and** ___ , "Brands as Beacons: A New Source of Loyalty to Multiproduct Firms," *Journal of Marketing Research*, 2004, *XLI*, 135–150.

Athey, Susan and Jonathan Levin, "Information and Competition in U.S. Forest Service Timber Auctions," *Journal of Political Economy*, 2001, *109(2)*, 375–417.

___ **and Philip A. Haile**, "Identification of Standard Auction Models," *Econometrica*, 2002, *70(6)*, 2107–2140.

Bajari, Patrick and Ali Hortaçsu, "Economic Insights from Internet Auctions," *Journal of Economic Literature*, June 2004, *42*, 457–486.

___ **and** ___ , "Winner's Curse, Reserve Prices and Endogenous Entry: Empirical Insights from eBay," *RAND Journal of Economics*, Summer 2003, *3(2)*, 329–355.

Balakrishnan, N. and William W.S. Chen, *Handbook of Tables for Order Statistics from Lognormal Distributions with Applications*, Dordrecht: Kluwer Academic Publishers, 1999.

Capen, E.C., R.V. Clapp, and W.M. Campbell, "Competitive Bidding in High-Risk Situations," *Journal of Petroleum Technology*, 1971, *23(6)*, 641–653.

Cox, James C., Sam Dinkin, and James T. Swarthout, "Endogenous Entry and Exit in Common Value Auctions," *Experimental Economics*, 2001, *4*, 163–181.

Donald, S. and Harry J. Paarsch, "Piecewise Pseudo-Maximum Likelihood Estimation in Empirical Models of Auctions," *International Economic Review*, 1993, *34*, 121–148.

Dyer, D., John H. Kagel, and Dan Levin, "A Comparison of Naïve and Experienced Bidders in Common Value Offer Auctions: A Laboratory Analysis," *Economic Journal*, 1989, *99*, 108–115.

Eaton, David H., "Valuing Information: Evidence from Guitar Auctions on Ebay," 2002. http://campus.murraystate.edu/academic/faculty/ david.eaton/workpaper0201.pdf.

Elyakime, B., Jean-Jacques Laffont, P. Loisel, and Quang Vuong, "First-Price, Sealed-Bid Auctions with Secret Reservation Prices," *Annales d'Economie et de Statistique*, 1994, *34*, 115–141.

Goeree, Jacob K. and Theo Offerman, "Efficiency in Auctions with Private and Common Values: An Experimental Study," *The American Economic Review*, 2002, *92(3)*, 625–643.

Guerre, Emmanuel, Isabelle Perrigne, and Quang Vuong, "Optimal Nonparametric Estimation of First-Price Auctions," *Econometrica*, 2000, *68*, 525–574.

Haile, Philip A., Han Hong, and Matthew Shum, "Nonparametric Tests for Common Values in First-Price Auctions," 2003. NBER working paper #10105.

Harstad, Ronald M. and Michael H. Rothkopf, "An Alternating Recognition Model of English Auctions," *Management Science*, 2000, *46(1)*, 1–18.

Hendricks, Kenneth and Robert H. Porter, "An Empirical Study of an Auction with Asymmetric Information," *The American Economic Review*, 1988, *78(5)*, 865–883.

____ **, Joris Pinkse, and Robert H. Porter**, "Empirical Implications of Equilibrium Bidding in First-Price, Symmetric, Common Value Auctions," *Review of Economic Studies*, 2003, *70-1;242*, 115–146.

——, **Robert H. Porter, and B. Boudreau**, "Information, Returns, and Bidding Behavior in OCS Auctions: 1954-1969," *Journal of Industrial Economics*, 1987, *35(4)*, 517–542.

Hong, Han and Matthew Shum, "Increasing Competition and the WinnerŠs Curse: Evidence from Procurement," *Review of Economic Studies*, October 2002, *69*, 871–898.

Houser, Daniel and John Wooders, "Reputations in Auctions: Theory, and Evidence from eBay," 2000. http://bpa.arizona.edu/ jwooders/revision.pdf.

Jin, Ginger Zhe and Andrew Kato, "Consumer Frauds and the Uninformed: Evidence from an Online Experiment," December 2004. http://www.glue.umd.edu/

Judd, Kenneth L., *Numerical Methods in Economics*, Cambridge, MA: MIT Press, 1998.

Kagel, John H. and Dan Levin, "The Winner's Curse and Public Information in Common Value Auctions: Reply," *The American Economic Review*, 1991, *81*, 362–369.

——, ——, **and J.F. Richard**, "Revenue Effects and Information Processing in English Common Value Auctions," *American Economic Review*, 1996, *86(3)*, 442–460.

——, ——, **and Ronald M. Harstad**, "Comparative Static Effects of Number of Bidders and Public Information on Behavior in Second-Price Common Value Auctions," *International Journal of Game Theory*, 1995, *24(3)*, 293–319.

Klein, Benjamin and Keith B. Leffler, "The Role of Market Forces in Assuring Contractual Performance," *Journal of Political Economy*, 1981, *89(4)*, 615–641.

Kremer, Ilan and Matthew Jackson, "On the Informational Inefficiency of Discriminatory Price Auctions," *Journal of Economic Theory*, September 2, 2004 online.

Laffont, Jean-Jacques and Quang Vuong, "Structural Analysis of Auction Data," *The American Economic Review, Papers and Proceedings*, 1996, *86(2)*, 414–420.

———, **Hervé Ossard, and Quang Vuong**, "Econometrics of First-Price Auctions," *Econometrica*, 1995, *63(4)*, 953–980.

Li, Tong, Isabelle Perrigne, and Quang Vuong, "Conditionally Independent Private Information in OCS Wildcat Auctions," *Journal of Econometrics*, 2000, *98(1)*, 129–161.

———, ———, **and** ———, "Structural Estimation of the Affiliated Private Values Auction Model," *Rand Journal of Economics*, 2002, *33(2)*, 171–193.

Lind, Barry and Charles R. Plott, "The Winner's Curse: Experiments with Buyers and with Sellers," *The American Economic Review*, 1991, *81*, 335–346.

Livingston, Jeffrey, "How Valuable Is a Good Reputation? A Sample Selection Model of Internet Auctions," 2002. http://www.cramton.umd.edu/workshop/papers/livingston-ebay-reputation.pdf.

McAfee, R. Preston, Wendy Takacs, and Daniel Vincent, "Tarrifying Auctions," *Rand Journal of Economics*, 1999, *30*, 158–179.

McDonald, Cynthia and V. Carlos Slawson Jr., "Reputation in an Internet Auction Market," *Economic Inquiry*, 2002, *40(4)*, 633–650.

McMillan, John and Eiichiro Kazumori, "Selling Online versus Offline: Theory and Evidence from Sotheby's," 2002. Mimeograph, Stanford University.

Mead, Walter J., Asbojrn Moseidjord, and Philip E. Sorenson, "The Rate of Return Earned by Leases Under Cash Bonus Bidding in OCS Oil and Gas Leases," *Energy Journal*, 1983, *4(4)*, 37–52.

Melnik, Mikhail and James Alm, "Does a Seller's E-Commerce Reputation Matter? Evidence from eBay Auctions," *Journal of Industrial Economics*, 2002, *50*, 337–349.

Milgrom, Paul, "A Convergence Theorem for Competitive Bidding with Differential Information," *Econometrica*, 1979, *47*, 679–688.

——— **and Robert Weber**, “A Theory of Auctions and Competitive Bidding,” *Econometrica*, 1982, *50*, 1089–1122.

Mood, Alexander M., Franklin A. Graybill, and Duane C. Boes, *Introduction to the Theory of Statistics*, New York: McGraw-Hill, Inc. 3rd Edition, 1974.

Paarsch, Harry J., “Deciding Between the Common and Private Value Paradigms in Empirical Models of Auctions,” *Journal of Econometrics*, 1992, *51*, 191–215.

Perry, Motty and Philip J. Reny, “On the Failure of the Linkage Principle in Multi-Unit Auctions,” *Econometrica*, 1999, *67(4)*, 895–890.

Pinkse, Joris and Guofu Tan, “Fewer Bidders Can Increase Price in First-Price Auctions with Affiliated Private Values,” 2000. working paper, University of British Columbia.

Reiley, David, Doug Bryan, Naghi Prasad, and Daniel Reeves, “Pennies from eBay: The Determinants of Price in Online Auctions,” 2000. http://www.vanderbilt.edu/econ/reiley/papers/PenniesFromEBay.pdf.

Resnick, Paul, Richard Zeckhauser, John Swanson, and Kate Lockwood, “The Value of Reputation on eBay: A Controlled Experiment,” March 12, 2004. http://www.si.umich.edu/ presnick/papers/postcards/.

Rothkopf, Michael H., “A Model of Rational Competitive Bidding,” *Management Science*, 1969, *15*, 362–373.

Shapiro, Carl, “Premiums for High Quality Products as Returns to Reputations,” *The Quarterly Journal of Economics*, 1983, *98(4)*, 659–679.

Wilson, Robert, “A Bidding Model of Perfect Competition,” *Review of Economic Studies*, 1977, *4(3)*, 511–518.

Yin, Pai-Ling, “A Survey-Based Procedure for Measuring Unobservable Information,” March 2005. Working Paper.